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Gibson-Poole, S; Humphris, Sonia; Toth, Ian K; Hamilton, A

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SRUC

Simon Gibson-Poole[1,2], S. Humphris[3], I. Toth[3], A. Hamilton[1]

[1]Scotland's Rural College, West Mains Road, Edinburgh, EH9 3JG, Scotland

[2]University of Edinburgh, Alexander Crum Brown Road, Edinburgh, EH9 3FF, Scotland

[3]The James Hutton Institute, Invergowrie Dundee DD2 5DA, UK.

Email: Simon.Gibson-Poole@sruc.ac.uk

www.sruc.ac.uk

Introduction

Unmanned Aerial Vehicles (UAV) have become useful and affordable research tools that show great promise for a variety of precision agriculture applications due to the unique aerial prospective they can provide (Shahbazi *et al.* 2014). In Scotland Blackleg disease is largely caused by *Pectobacterium atrosepticum* (*Pba*), via contaminated seed tubers (Skelsey *et al.* 2016). Worldwide, blackleg disease is a major contributor to the loss of potato crops and checking for its presence is time consuming and can inadvertently damage the crop canopy. Therefore this project was initiated to answer the question:

- Can the onset of black disease be detected using a UAV equipped with commercial off-the-shelf (COTS) digital cameras?

Trial Layout and Aerial Capture Methods

32 drills of potatoes containing 12 tubers in each (Fig.1a) were planted on 5/5/2016 and surveyed regularly across the growing season using a custom built UAV carrying two COTS digital cameras, with one modified to capture near infra-red (NIR) wavelengths of light (Fig. 1b).

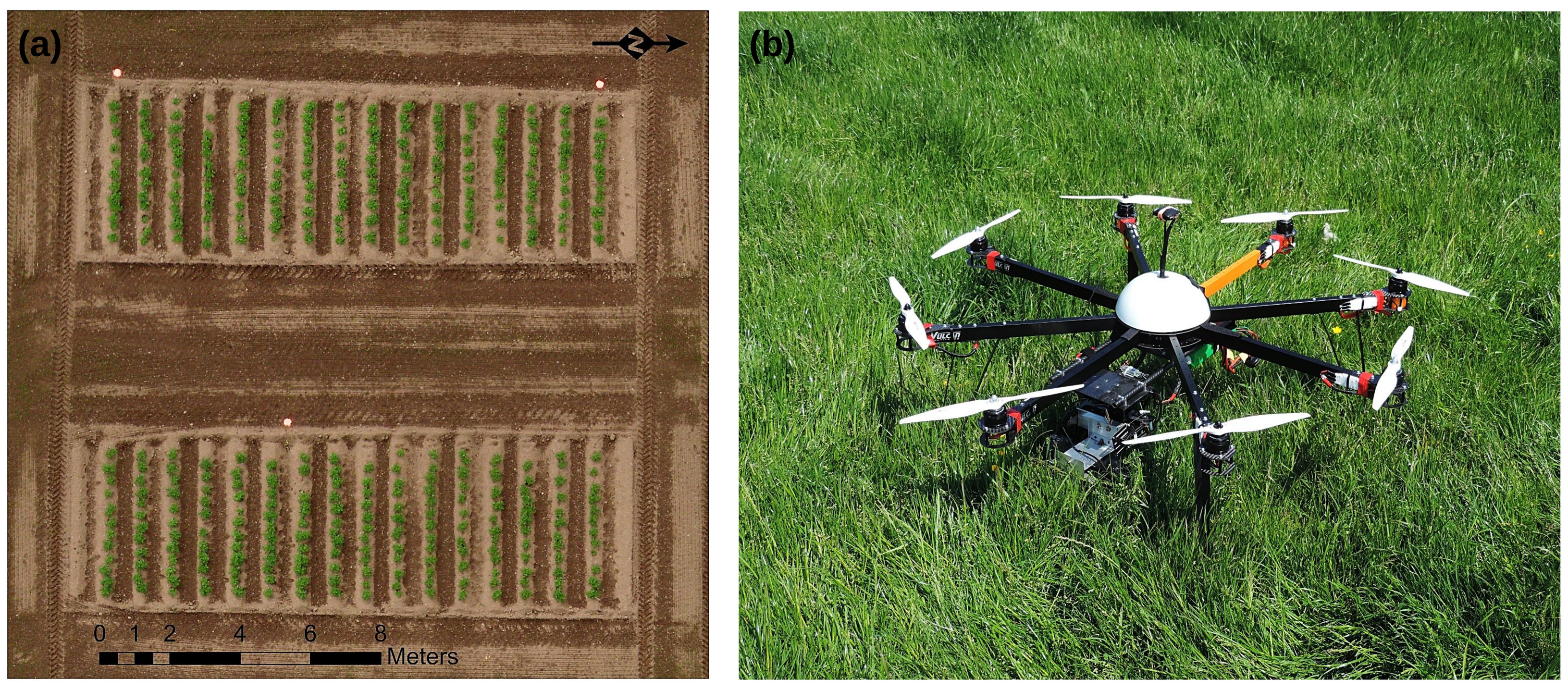

Figure 1. (a) The trial plot layout on 21/6/2016; (b) The custom built Vulcan multi-rotor UAV.

The tubers planted had been exposed to *Pba* to ensure the onset of disease and a ground truth visual assessment of the plots was conducted towards the end of the growing season to identify any diseased plants. Each aerial survey was conducted at 35 m above ground level to give a ground sample distance of ~1 cm per pixel and georectification was achieved using nine ground control points surveyed using a Piksi GPS system to an expected accuracy of ±13 cm.

The RAW imagery from the cameras was processed linearly and orthorectified using structure from motion (SfM) techniques to give true colour and NIR orthomosaics for each survey date, as well as digital surface and terrain models that were processed further to give an estimation of crop height.

Emergence Analysis

The data from each survey was analyzed visually initially and then automatically using a pixel based approach that used a simple growth model to allow plants emerging at different dates to be identified (Fig. 2). 385 emerged plants were detected using both methods and all plants had emerged by 21/6/2016 however two cases of non-emergence and three extra plants were discovered (left over tubers had been planted). Emergence detection agreement between visual and automatic analysis by date was high, resulting in a total accuracy (TA) of 95% and Kappa coefficient (K) of 0.88.

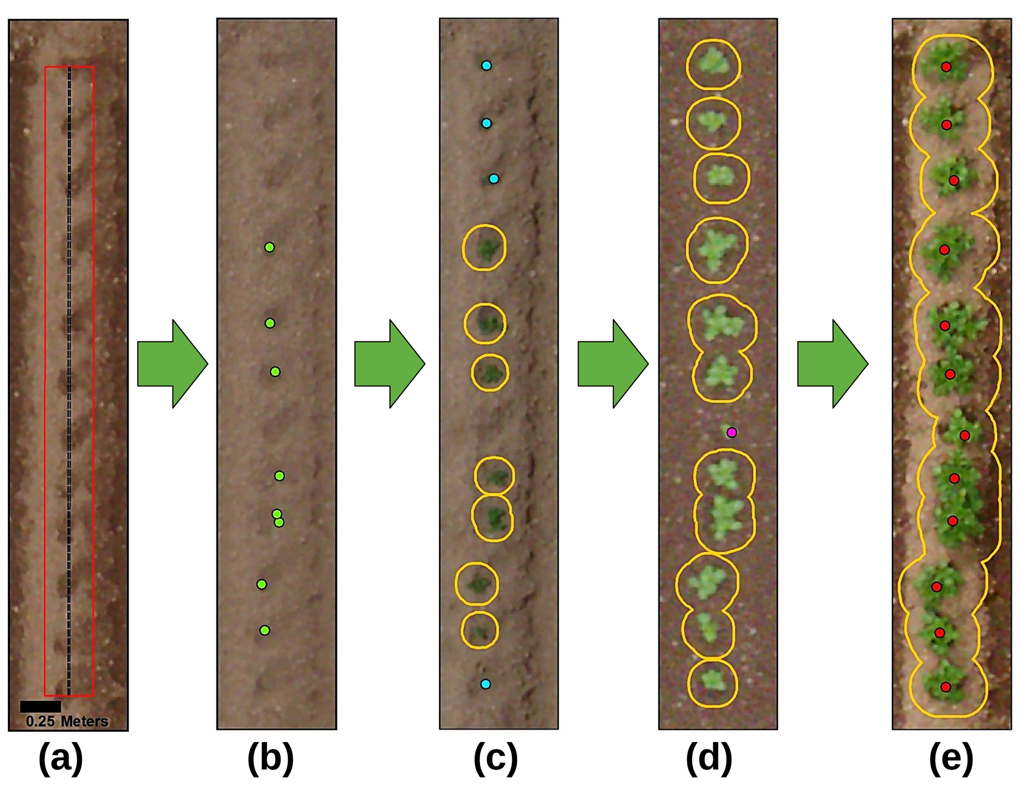

Figure 2: (a) 27/5/2016 - The centre line of the drill is identified (black line) and a region of interest is marked (red box); (b) 2/6/2016 - The first emerging plants are marked (green dots); (c) 7/6/2016 – More plants are noted (blue dots) but those under a buffer (orange) created from the vegetation identified in the previous date are ignored; (d) 13/6/2016 – Further plants are marked (pink dots) using the same method; (e) 21/6/2016 – All plants have emerged within the region of interest, any close together are merged (red dots).

Disease Detection Analysis

The emergence points were used to denote regions of interest for each plant using Thiessen polygons (Fig. 3a). Initial visual analysis of each survey was conducted with the assessor making use of true and false colour orthomosaics to identify diseased plants. Automatic analysis used an object based image analysis approach to classify potato vegetation and flowers per drill, which fed into a model that marked plants as diseased if they showed slower vegetation ground cover growth and a mean height one standard deviation lower than the grand mean height of all the plants for that sensing date (Fig. 3).

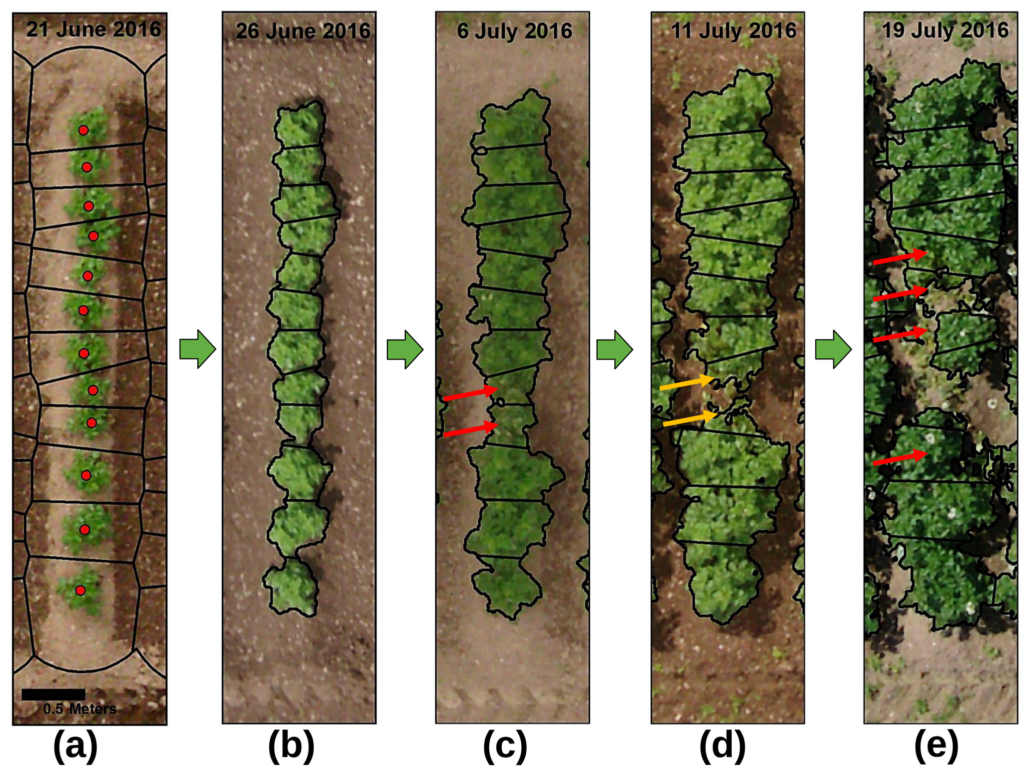

Figure 3: (a) Emergence points (red dots) used to create regions of interest for each plant using Thiessen polygons (black borders); (b) 26/6/2016 - No disease detected; (c) 6/7/2016 – Disease detected for two plants showing low growth and lower than average height (red arrows); (d) 11/7/2016 – No new disease detected but infected plants die back (orange arrows); (e) 19/7/2016 – Four more plants are showing signs of disease (red arrows), both large canopy loss and reduced canopy growth with lower than average height.

Results

The ground truth conducted on the 14/7/2016 (and updated to include obvious diseased plants on the 19/7/2016), indicated that 98 plants showed signs of disease, caused by *Pba* and other infections. Visual analysis detected 80 diseased plants with no false positives and automatic analysis detected 115 diseased plants, with 83 being valid and 32 false positives (Table 1, Fig. 4).

Table 1: Disease detection accuracy of visual and automatic methods verses ground truth, showing expected number of diseased plants (E), observed number of diseased plants (O), correctly identified diseased plants (C), Producers (PA), Users (UA) and Total accuracy (TA), along with Kappa statistic to indicate level of agreement.

Disease detection comparison	E	O	C	PA	UA	TA	Kappa
Ground Truth vs Visual Analysis	98	80	80	82 %	100 %	95 %	0.87
Ground Truth vs Automatic Analysis	98	115	83	85 %	72 %	88 %	0.70

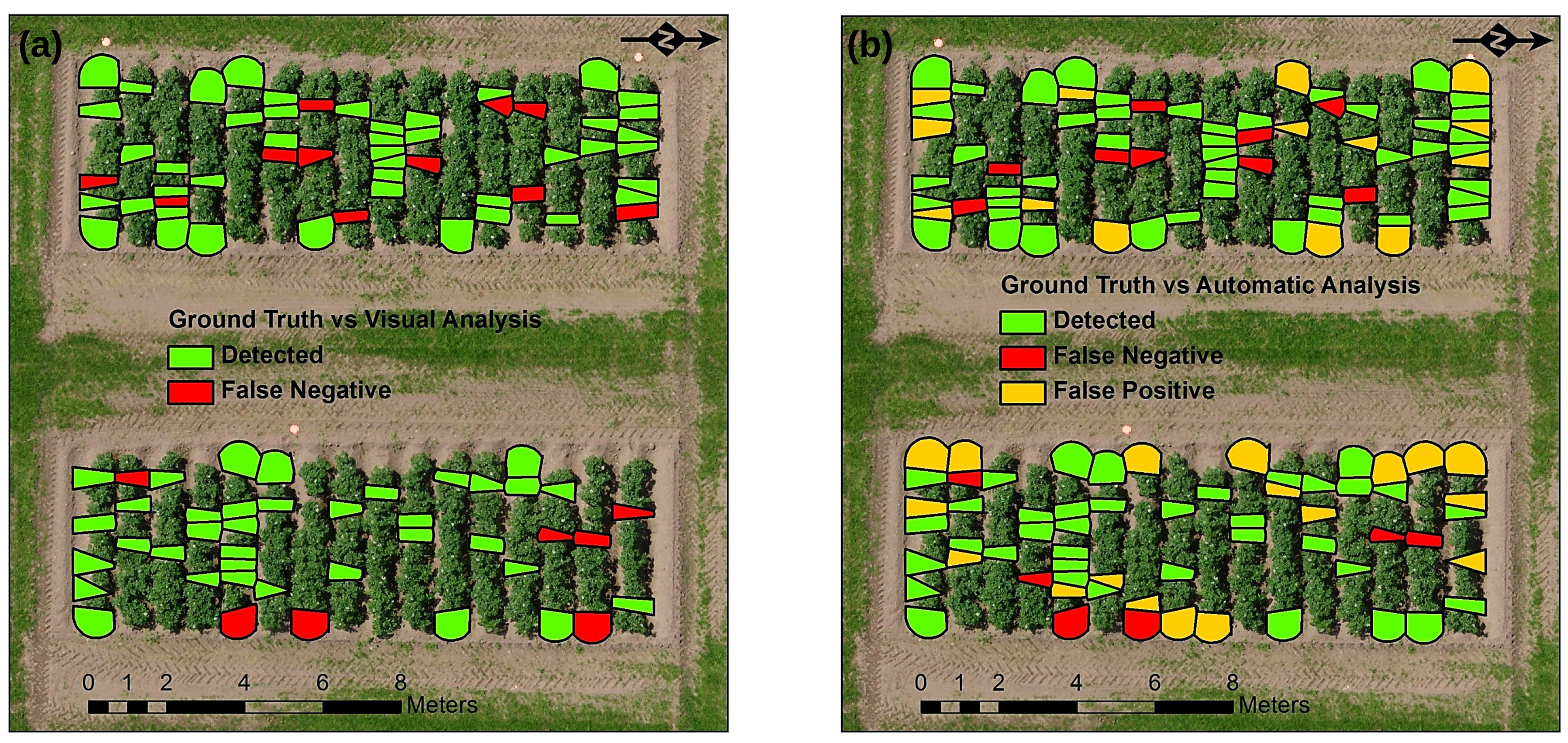

Figure 3: (a) Disease detection agreement between ground truth and visual assessment; (b) Disease detection agreement between ground truth and automatic analysis.

Conclusions

- The type of disease effecting a plant could not be determined.
- Visual analysis of UAV generated imagery is effective at identifying disease, but only when it has started to affect the canopy of the plant.
- Automatic analysis tended to detect disease slightly earlier due to using height information but produced more false positive results.
- A more accurate GPS system onboard the UAV would eliminate the need for ground control points and could reduce the number of false positives by improving image alignment between sensing dates.

Acknowledgements and references

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